Retail Inventory Productivity: Analysis and Benchmarking

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Vishal Gaur
Department of IOMS
Stern School of Business, New York University
8-72, 44 West 4th St.
New York, NY 10012
Ph: 212 998-0297, Fax: 212 995-4227
E-mail: vgaur@stern.nyu.edu

Marshall Fisher
Department of Operations and Information Management
The Wharton School, University of Pennsylvania
Suite 1300, 3620 Locust Walk,
Philadelphia, PA 19104-6366
Ph: 215 898-7721, Fax: 215 898-3664
E-mail: fisher@wharton.upenn.edu

Ananth Raman
Harvard Business School
T-11, Morgan Hall
Soldiers Field
Boston, MA 02163
Ph: 617 495-6937, Fax: 617 496-4059
E-mail: araman@hbs.edu

Abstract

Retail inventory productivity is of considerable interest to retailers, manufacturers and distributors who service them, and stock market analysts. Inventory turnover is frequently used to measure inventory productivity. We find wide variation in inventory turnover across retailers and over time. The causes of this variation have not been studied systematically to our knowledge. We develop a log-linear empirical model to quantify the impact of net markup, capital intensity and deviation of sales from forecast on the variation in inventory turnover and test it on a panel of data for 311 firms for the years 1985-2000. The model explains 66.7% of the within-firm variation and 97.2% of the total variation in inventory turnover. The average estimates of the coefficients of net markup, capital intensity and sales surprise across all retailing segments are -0.24, 0.25 and 0.14, respectively. We define an alternative metric of inventory productivity, adjusted inventory turnover, which adjusts inventory turnover for changes in net markup, capital intensity and deviation of sales from forecast. We discuss several examples where inventory turnover and adjusted inventory turnover give contradictory results. We also compute time-trends in inventory productivity, and find that it has declined in the retailing industry during 1985-2000.

1. Introduction

Retailers in the United States carried approximately $400 billion in inventory in 2002 according to the census bureau's Monthly Retail Trade Surveys. Inventory typically represents about 36% of total assets and 53% of current assets for retailers[1]. Not surprisingly, retailers and stock market analysts focusing on retailers pay close attention to inventory productivity.

Inventory turnover, the ratio of a firm's cost of good sold to its average inventory level, is frequently used to compare inventory productivity across retailers and over time. However, inventory turnover has several shortcomings. First, changes in inventory turnover can be correlated with changes in price, variety and investment in supply chain infrastructure. For example, consider a retailer whose inventory turnover decreased from 5/year to 4/year while its average markup, the ratio of gross margin to cost of goods sold, increased from 75% to 100%. Since inventory turnover and markup have changed in opposite directions, it is unclear if the inventory productivity of the retailer has increased or decreased. Second, inventory turnover can change due to the deviation of sales outcome from the forecast. If the sales outcome is higher than the forecast then the retailer will observe higher inventory turnover. Such changes in inventory turnover may not indicate improvements in inventory productivity. Third, we find that annual inventory turnover in the U.S. retailing industry varies widely over time and across firms. For example, during 1985-2000, the inventory turnover at Best Buy Stores, Inc. ranged from 4.15 to 8.93, at Gap, Inc. from 5.31 to 8.98, and at Wal-Mart Stores from 5.68 to 8.65. We computed the variation in inventory turnover across years for each firm in our dataset as the ratio of its maximum to minimum annual inventory turnover. This ratio ranged between 1.83 and 263 across firms. The differences in inventory turnover across firms in any given year are even larger, e.g., the annual inventory turnover of supermarket chains in year 2000 ranges between 4.7 and 19.5. The causes of the variation in inventory turnover have not been studied systematically to our knowledge.

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[1] These values are computed from our dataset, which contains quarterly values of inventory, total assets, current assets and other variables for all public retailers across 10 product-market segments for the period 1985-2000. The dataset includes 311 firms. It is constructed using Standard and Poor's Compustat database and is summarized in section 2.

This paper presents an empirical model to quantify the impact of various operational characteristics on the variation in retail inventory turnover using public financial data. We identify the following variables that should be correlated with inventory turnover and can be measured from public financial data: net markup (the ratio of gross margin net of markdowns to cost of goods sold), capital intensity (the ratio of average fixed assets to average total assets), and sales surprise (the deviation of the sales outcome from the forecast for the year). Using results from the existing literature, we formulate hypotheses to relate these variables to inventory turnover. We argue that net markup determines optimal stocking level and thus inventory turnover according to mathematical inventory models. Further, net markup is affected by product variety, shortness of product lifecycle and markdowns, each of which should be correlated with inventory turnover. Thus, we formulate the hypothesis that changes in inventory turnover should be correlated with changes in net markup. Similarly, capital intensity, which includes investment in fixed assets like warehouses and information technology, should be positively correlated with inventory turnover. Lastly, sales surprise, which would result in a decrease in inventory level, should be positively correlated with inventory turnover. We formulate an empirical model to represent these relationships and apply it to the panel of retailing data.

Our paper reports three main findings. First, we find that the explanatory variables explain 66.7% of the variation in inventory turnover *within* a firm and 97.2% of the *total* variation in inventory turnover (i.e., within and across firms). On average, across all retailing segments, a 1% increase in net markup is associated with 0.24% decline in inventory turnover, a 1% increase in capital intensity is associated with 0.25% increase in inventory turnover, and a 1% sales surprise is associated with a 0.14% average increase in inventory turnover. The coefficients are consistent across a range of econometric models with different control variables and different assumptions about the error term.

Second, using our model, we derive an alternative metric of inventory productivity, Adjusted Inventory Turns, which adjusts inventory turns for changes in net markup, capital intensity, sales surprise and time-trends, and use this metric to evaluate changes in inventory productivity over time. We identify firms (e.g. Ruddick Corporation) where adjusted inventory turns have improved during a period when inventory turns declined. We also use this metric to compare performance across firms. We identify firms (e.g. Charming Shoppes and Chico's Fas, Inc.) whose inventory turns are similar but adjusted inventory turns differ considerably, and other firms (e.g., Casual Male Retail Group and Syms Corp.) whose inventory turns differ much more than their adjusted inventory turns.

Third, we estimate whether the inventory productivity of retailers has improved with time and with investment in technology. We find that inventory turnover and adjusted inventory turnover have both decreased significantly during the period 1985-2000. However, capital intensity has increased during this period and has strong positive correlation with inventory turnover. Thus, in spite of the overall trend, firms that have invested more in capital assets have achieved higher gains in inventory productivity.

Many researchers have expressed interest in time-trends in inventory and inventory turnover in order to evaluate the impact of new technology, process innovations, and developments in inventory theory. For example, Hopp and Spearman (1996: chapter 5) discuss whether firms in the U.S. manufacturing industry that implemented MRP systems achieved better inventory turns as a result; Rajagopalan and Malhotra (2001) determine whether inventories in the U.S. manufacturing industry have decreased with time. However, there is relatively little empirical research on evaluating inventory productivity at the firm level. We use firm level panel data in this paper, which is advantageous in several ways. First, heterogeneity across firms in panel data enables us to separate the effects of the explanatory variables from time-trends caused by changes in economic conditions and the effects of latent characteristics of firms such as differences in accounting policies. Second, time-series data for each firm can be used to measure how changes in inventory turnover are correlated with simultaneous changes in net markup, capital intensity and sales surprise within the firm. Third, compared to aggregate industry data, firm-level data control for unequal time-histories caused by the entry and exit of firms, and thus, give more accurate estimates of time-trends in inventory turnover. Fourth, panel data allow several econometric specifications with different control variables and assumptions about the error term. For example, we test firm-specific and time-specific fixed effects, interaction effects and differences in coefficients across retailing segments and across years. Thus, we obtain more accurate estimates of the relationship of inventory turnover with the explanatory variables than possible with aggregate data or with purely time-series or cross-sectional data.

This paper is organized as follows. In §2, we summarize the data and define the performance variables used. In §3, we develop and estimate an econometric model to relate inventory turnover with net markup, capital intensity and sales surprise. In §4, we compute time-trends in inventory productivity and describe the use of 'adjusted inventory turnover' to compare inventory productivity across firms and over time. Finally, in §5, we discuss the limitations of our model and avenues for future research.

2. Definition of Variables

We use financial data for all public listed U.S. retailers for the 16-year period 1985-2000 drawn from their annual income statements and quarterly and annual balance sheets. The data are obtained from Standard & Poor's Compustat database.

The selection of firms is based on a four-digit Standard Industry Classification (SIC) code assigned to each firm by the U.S. Department of Commerce according to its primary industry segment. Our dataset includes the following ten segments in the retailing industry: apparel and accessories, catalog and mail-order, department stores, drug stores, supermarkets and convenience stores, hobby toys and game stores, home furniture and equipment stores, jewelry stores, consumer electronics stores, and variety stores. Table 1 lists the segments, the corresponding SIC codes, and examples of firms in each segment. All segments except apparel and accessories and food stores correspond to unique 4-digit SIC codes. In apparel and accessories, we group together all firms that have SIC codes between 5600 and 5699 because there is substantial overlap between the products sold by them. These SIC codes correspond to men's, women's and children's clothing stores, family clothing stores and shoe stores. This grouping enables us to increase the number of degrees of freedom by estimating one set of coefficients for all apparel firms instead of estimating separate coefficients for each SIC code. Likewise, in food stores, we group together supermarket chains (SIC code 5400) and convenience stores (SIC code 5411) because of the overlap between their products.

Appendix 1 lists the definitions of the variables used in this paper. After computing the values of the variables, the first two years of data for each firm are omitted. They cannot be used in the analysis because the computation of sales forecast requires two years of sales data at the beginning of each time-series. We also omit from our dataset those firms that have less than five consecutive years of data available for any sub-period during 1985-2000; there are too few observations for these firms to conduct time-series analysis. Finally, we omit those firms that had missing data other than at the beginning or end of the measurement period. Our final dataset contains 3407 observations across 311 firms, an average of 10.95 years of data per firm. Table 2 presents summary statistics by retailing segment for the performance variables used in our study. It lists the mean and standard deviation for each variable within each segment.

3. Analysis of Retail Inventory Turnover

In this section, we develop and estimate an econometric model to relate inventory turnover with net markup, capital intensity and sales surprise for a given firm. We present the hypotheses in §3.1, set up the model to test these hypotheses in §3.2, and discuss estimation results in §3.3.

We focus attention on a single firm and consider year-to-year changes in the values of the variables for the firm. Even though our dataset contains multiple firms, our model will examine variation within a firm by using firm-specific fixed effects to control for differences across firms. Thus, the hypotheses cannot be applied to differences in the values of the variables across firms because such differences may be caused by factors not included in the hypotheses, such as the accounting policies of firms.

3.1 Hypotheses

3.1.1 Changes in net markup

In this section, we consider the firm's decisions on markup, amount of variety, length of product lifecycle, markdowns, and inventory quantity. We show that net markup should affect inventory turnover directly because it determines the optimal service level. Further, net markup should be related to inventory turnover indirectly through product variety, length of product lifecycle and markdowns because they affect both inventory turnover and net markup. On the basis of this analysis, we expect inventory turnover and net markup to be correlated with each other, and formulate hypothesis 1 as below. The sign of the correlation cannot be predicted a priori because we find that different factors affecting inventory turns and net markup imply different directions of correlation between these variables. Hereafter, 'markup' and 'net markup' are used interchangeably.

HYPOTHESIS 1: A retailer's inventory turnover is correlated with its net markup.

We also note that there is ample evidence that firms modify their variety, product lifecycle characteristics, pricing strategies and markdown policies over time. For example, Best Buy Stores, Inc., radically altered its pricing strategy and the amount of variety in its stores in three phased projects during 1983-95 (Kasturi Rangan and Chakravarthy 1997); Wal-Mart Stores expanded the amount of variety in its stores during the 1990s by converting them to a supercenter format (Bradley, et al. 1996); and Gap, Inc., continuously chooses the mix of 'basic' apparel (longer lifecycle) and 'fashion' apparel (shorter lifecycle) to carry in each of its retail formats, and the fashion component in its offering changes as the company develops new formats such as Old Navy and Banana Republic (Salmon and Wylie 2001). The implications of these factors on inventory turnover and net markup are as follows.

Service Level: An increase in markup implies a decrease in inventory turnover for a firm making optimal inventory decisions according to the classical newsboy model. Higher markup implies a higher critical fractile, which implies a higher inventory level. In appendix 2, we show that expected inventory turnover decreases with the increase in inventory level in the newsboy model with any demand distribution. Therefore, the increase in markup implies a decrease in expected inventory turnover.

Product Variety: We argue that higher product variety can be expected to lead to higher markup and lower inventory turnover.

Multiple papers in marketing and economics have explained the effect of product variety on markup. Lancaster (1990), Chamberlin (1950) and Dixit and Stiglitz (1977) have argued that consumers derive greater utility when variety is higher. In the Lancaster demand model, an increase in variety results in an increase in consumer utility because it reduces the distances of consumers from their perceived 'ideal product' profile. In the Chamberlin demand model, an increase in variety results in an increase in consumer utility because consumers have an in-built preference for variety. From consumer utility theory (Kotler 1986, Nagle 1987), higher consumer utility implies higher prices for a given cost, and thus, higher markup.

Lazear (1986) also explains the effect of product variety on markup using a model of retail pricing and clearance sales. He shows that average markup increases with the increase in retailer's uncertainty about price. He illustrates this result by comparing the pricing policies for men's and women's clothing: assuming that women's clothing has more variety than men's clothing, he shows that it will have a higher average markup than men's clothing.

Pashigian (1988) and Kekre and Srinivasan (1990) provide statistical evidence for the effect of variety on markup. Pashigian uses time-series price and sales data for department stores to test Lazear's theory of clearance sales. He shows that average annual markup is positively correlated with variety. Kekre and Srinivasan, in a cross-sectional study of inter-firm performance, use a sample of over 1,400 business units to show that firms with higher variety have higher relative prices.

Numerous papers and case studies using risk pooling as the basis of their argument have examined the impact of product variety on inventory turnover. For example, Zipkin (2000: chapter 5) constructs an index of product variety and discusses its effect on inventory turnover using detailed data from a large firm. He finds that an increase in variety is associated with a decrease in inventory turnover. In the Benetton case study, lower variety through delayed differentiation is used to increase inventory turnover (Heskett and Signorelli 1989). Similar insights are also derived at Hewlett-Packard (Feitzinger and Lee 1997), and in research articles that explore these relationships (Lee and Tang 1997, Swaminathan and Tayur 1998). Under the commonly used risk-pooling argument, average inventory increases with variety in the square root of the number of items. It implies that expected inventory turnover is decreasing in the amount of product variety.

Van Ryzin and Mahajan (1999) also analyze the effects of variety on price and inventory using a model of assortment choice and inventory decisions under consumer choice based demand. While they do not explicitly consider inventory turnover, they show that the total inventory increases with variety, and that higher prices are optimal for a firm that offers greater variety under market equilibrium given fixed procurement cost.

Length of the product lifecycle: Like higher variety, a reduction in the length of product lifecycle should also result in an increase in expected markup of a firm and a decrease in expected inventory turnover.

A shorter product lifecycle implies rapid changes to products to better match consumer requirements, and thus, increases higher consumer utility (Pashigian 1988). From Kotler (1986) and Nagle (1987), higher consumer utility implies higher prices and higher markup.

A shorter product lifecycle also implies greater demand uncertainty. Eppen and Iyer (1997) and Fisher and Raman (1996) show that the accuracy of demand forecasts increases with the availability of historical data. Better forecast accuracy implies that less safety stock is required for the same expected sales. Thus, products with longer lifecycle and greater availability of historical data should have lower demand uncertainty and higher inventory turnover than products with shorter product lifecycle and less availability of historical data.

Markdowns: The three factors considered above, service level, product variety and length of product lifecycle, are decided before a stocking decision is made. Markdowns differ in the respect that they are undertaken after observing partial demand. We show that markdowns may imply a positive correlation between inventory turnover and net markup. Thus, the direction of the relationship between inventory turnover and net markup taking into account the effects of service level, product variety, length of product lifecycle and markdowns cannot be predicted a priori.

Markdowns are expected to decrease net markup and increase sales. Due to the increase in sales, the inventory level is reduced and inventory turnover is increased. However, since markdowns are applied after observing partial demand, more markdowns may be applied if demand is below forecast than if demand is above forecast. Thus, depending on the deviation of demand from forecast, the firm may realize higher net markup and higher inventory turnover if demand is above forecast than if it is below forecast. Therefore, markdowns may imply a positive correlation between inventory turnover and net markup.

3.1.2 Changes in capital intensity

The factors that increase the capital intensity of a retailer can be expected to improve its inventory turnover. These factors include adding a new warehouse, installing an information technology system, or installing an inventory and logistics management system. They involve capital investment by a firm, which is accounted as fixed assets, and therefore, is measured by an increase in the ratio CI_{sit}. Thus, we formulate the following hypothesis:

HYPOTHESIS 2: A retailer's inventory turnover is positively correlated with its capital intensity.

We expect that the addition of a new warehouse should result in a decrease in total inventory at the retailer, and thus, an increase in its inventory turnover because of two reasons: (i) the warehouse enables the retailer to reduce safety stock over the supplier lead-time, (ii) the warehouse enables the retailer to centralize safety stock and re-balance store inventories between shipments from the supplier. Eppen and Schrage (1981) have studied the first effect, and called it 'the joint ordering effect'. They consider a system with one supplier, one warehouse and several stores, with production and transportation lead-times. The warehouse places orders with the supplier, receives shipments, and allocates them to the stores, but does not store any inventory. Comparing this system with a decentralized system where stores independently place orders with the supplier and receive direct shipments, they show that the warehouse reduces the total system inventory by letting the retailer postpone the decision of allocating inventory across stores.

The second effect is called 'the depot effect' and has been studied by several researchers. For example, Jackson (1988) considers an extension of the model of Eppen and Schrage where the warehouse is allowed to hold inventory. He shows that this enables the warehouse to centralize safety stock and further postpone the allocation of inventory across stores. He, thus, shows that the total system inventory is further reduced compared to the model considered by Eppen and Schrage. Therefore, due to these two effects, adding a warehouse should enable a retailer to reduce average inventory level and thus increase its inventory turnover.

We also expect inventory turns to increase with investment in information technology. Cachon and Fisher (2000) show that the benefits of implementing information systems for the management of inventory include better allocation of the inventory to the stores, shorter ordering lead times, smaller batch sizes, and a lower cost of processing orders. Clark and Hammond (1997), in a cross-sectional study, show that food retailers who adopt a continuous replenishment process (CRP) enabled by the adoption of electronic data interchange (EDI) achieve 50-100% higher inventory turns than traditional ordering processes. Other documentation of the benefits of information technology is found in Kurt Salmon Associates (1993), Campbell Soup Company (Cachon and Fisher 1997), Barilla SpA (Hammond 1994), H. E. Butt Grocery Co. (McFarlan 1997), and Wal-Mart Stores, Inc. (Bradley, et al. 1996).

Since investments in distribution centers, logistics, and information technology are included in the gross fixed assets of a firm, we use capital intensity as defined in section 2 as a proxy for the differences in technology across firms. We also considered an alternative measure of capital intensity using net fixed assets instead of gross fixed assets. This does not change the results of our paper.

3.1.3 Sales Surprise

We relate changes in inventory turnover to the difference between realized sales and forecasted sales. If the sales realized by a retailer in a given period are higher than the forecast for that year, then the end of period inventory level will be lower than expected. Thus, the average inventory level for the year will also be lower than expected, and realized inventory turnover, which is a ratio of realized unit sales to the average inventory for the period, will be higher than expected. On the other hand, if realized sales are lower than the forecast, then the average inventory level during the period will be higher than expected, resulting in lower realized inventory turnover.

As defined in section 2, we use the term 'sales surprise', denoted SS_{sit}, for the deviation of realized sales from the forecast. We compute sales surprise as the ratio of realized sales in a year to the sales forecast for that year. Therefore, we formulate the following hypothesis.

HYPOTHESIS 3: A retailer's inventory turnover is positively correlated with sales surprise.

We use Holt's linear exponential smoothing model to compute the sales forecast for each firm for each year. In this model, the sales forecast for period t is computed from historical observations as

$$\text{Sales Forecast}_{sit} = L_{si,t-1} + T_{si,t-1},$$

where $L_{si,t-1}$ and $T_{si,t-1}$ are smoothed series defined as

$$L_{sit} = \alpha S_{sit} + (1-\alpha)(L_{si,t-1} + T_{si,t-1}),$$
$$T_{sit} = \gamma(L_{sit} - L_{si,t-1}) + (1-\gamma)T_{si,t-1},$$

and α ($0 < \alpha < 2$) and γ ($0 < \gamma < 4/\alpha - 2$) are weighting constants. We computed the forecasts for several values of α and γ, and compared their forecast errors. We obtained the best forecasts for $\alpha = \gamma = 0.75$. Thus, these values are used to compute all the results reported in this paper. We also computed sales forecasts using simple exponential smoothing and double exponential smoothing. We found that these forecasting methods have higher forecast errors than Holt's linear exponential smoothing. However, we estimated our model using these forecasting methods and found that the results are consistent across all these methods. See Chatfield (2001) for a complete description of the forecasting methods.

We note that sales surprise should, ideally, be measured as the ratio of realized sales to the management's forecast because inventory decisions are based on the management's forecast. However, the management's forecast of sales is not reported publicly for all the firms in our dataset, and thus, could not be used in the analysis.

3.2 Model Specification and Estimation Methodology

3.2.1 Model Specification and Control Variables

We propose the following log-linear model with firm-wise, year-wise and segment-wise control variables to formulate the relationship between IT_{sit}, MU_{sit}, SS_{sit} and CI_{sit}.

$$\log IT_{sit} = F_i + c_t + b_s^1 \log MU_{sit} + b_s^2 \log CI_{sit} + b_s^3 \log SS_{sit} + \varepsilon_{sit}. \tag{1}$$

The parameters in this model are:

F_i = intercept for firm i;

c_t = time-specific fixed effect for year t;

b^1_s = coefficient of $\log MU_{sit}$ for segment s;

b^2_s = coefficient of $\log CI_{sit}$ for segment s;

b^3_s = coefficient of $\log SS_{sit}$ for segment s;

ε_{sit} = error term for the observation for year t for firm i in segment s.

Here, F_i are time-invariant firm-specific control variables, c_t are year-specific control variables and b^1_s, b^2_s, b^3_s are segment-specific coefficients. For each segment s, hypothesis 1 implies that b^1_s must be different from zero, hypothesis 2 implies that b^2_s must be greater than zero, and hypothesis 3 implies that b^3_s must be greater than zero.

In this section, we first explain why a log-linear relationship between the variables in our model is more suitable than a linear relationship. We then explain the use of firm-specific, time-specific and segment-specific control variables, and construct several alternative model specifications. In §4.2, we specify the structure of the variance-covariance matrix of ε_{sit} and describe the estimation methodology.

We use a log-linear model for three reasons: (1) A log-linear relationship between the variables is suggested by plotting IT against MU, CI and SS. (2) Surveys of retailers that we have conducted show that 'multiplicative measures' such as GMROI (gross margin return on inventory, computed as the product of IT and MU), return on assets and return on assets are widely used to measure and reward the performance of inventory planners and merchants. (3) We compared log-linear and linear specifications by simulation. We simulated a stylized periodic review inventory model with stationary demand for different values of markup, lead-time, and the standard deviation of demand. We fitted both log-linear and linear specifications to the dataset obtained from the simulation, and found that the log-linear specification had significantly lower prediction errors that the linear specification.

The firm-specific, time-specific and segment-specific control variables used in (1) are as follows.

Firm-specific control variables, F_i: These variables are required to control for differences in the intercept between firms. Such differences may be caused by characteristics such as managerial efficiency, marketing, location strategy, etc. They may also be caused by differences in accounting policies across firms, such as in their leasehold accounting and the treatment of selling commissions. Further, the explanatory variables, MU, SS and CI, may be correlated with F_i. Therefore, omitting F_i may result in biased and inconsistent estimates of the parameters (see Hausman and Taylor 1981). The correlation of the explanatory variables with F_i would also imply that cross-sectional data for a single year or longitudinal data for a single firm are unsuitable for estimating the model because they cannot distinguish the effects of the explanatory variables from the differences in F_i (see Hoch 1962).

F_i may be modeled either as fixed effects or as random effects. We model them as fixed effects because they can be used to compare average inventory turnover performance across firms over the period of analysis.

Time-specific control variables, c_t: These variables reflect changes in secular characteristics over time, such as in economic conditions, in the interest rates, in price level, etc. By controlling for such changes, they enable us to compare inventory turnover across years.

Segment-specific coefficient estimates, b^1_s, b^2_s, b^3_s: The coefficients of the explanatory variables may differ across retailing segments. Thus, we test for heterogeneity across segments by estimating different coefficients for each segment.

Various other model specifications with different combinations of the control variables can be explored to draw further insights from the model. For example, we test whether the coefficients of the explanatory variables differ across segments by comparing (1) with the following specification (which has pooled coefficients of explanatory variables instead of segment-wise coefficients).

$$\log IT_{sit} = F_i + c_t + b^1 \log MU_{sit} + b^2 \log CI_{sit} + b^3 \log SS_{sit} + \varepsilon_{sit}. \tag{2}$$

Similarly, we test whether the firm-wise fixed effects F_i are statistically significant by comparing (1) with the following specification (which has segment-wise fixed effects instead of firm-wise fixed effects).

$$\log IT_{sit} = F_s + c_t + b_s^1 \log MU_{sit} + b_s^2 \log CI_{sit} + b_s^3 \log SS_{sit} + \varepsilon_{sit}. \tag{3}$$

Here, F_s is the segment-wise fixed effect, and c_t is the year-specific fixed effect. Both (2) and (3) are useful because they have fewer parameters, which allow more precise estimation. However, (3) should not be used if firm-wise fixed effects are significant. Other model specification may be constructed to test if $b^1{}_s$, $b^2{}_s$ and $b^3{}_s$ change with time or if the time-specific fixed effect c_t differs across segments. We analyze the results of all these specifications in section 5. The main results of the paper are based on (1) and (2).

We refer the reader to Greene (1997: chapter 14), Hsiao (1986) and Judge, et al. (1985: chapter 13) for a complete discussion of the specification and estimation of panel data models.

3.2.2 Estimation methodology

Since our data contain observations across firms and years, it is likely that the variance of ε_{sit} varies across firms, and that ε_{sit} is correlated across years. Therefore, we consider a flexible structure of the variance-covariance matrix of ε_{sit} with segment-wise heteroscedasticity and first-order autocorrelation. Segment-wise heteroscedasticity implies that the variance of ε_{sit} is identical across firms within a retailing segment but differs across segments. Such differences are likely to arise because we find that the standard deviations of all the variables differ substantially across segments. For example, as shown in table 2, the standard deviation of inventory turnover ranges from a low of 0.58 for jewelry stores to a high of 10.42 for home furniture and equipment stores. Likewise, the standard deviation of markup ranges from a low of 0.12 for food stores to a high of 1.02 for catalog and mail-order houses.

Autocorrelation is also a common characteristic of financial time-series data. Since our data are annual time-series, we use a first-order autoregressive process; higher order autoregressive processes would be suitable for monthly or quarterly data.

Thus, for our model, the autoregressive process for ε_{sit} with segment-wise heteroscedastic variance is specified as

$$\varepsilon_{sit} = \rho_s \varepsilon_{si,t-1} + u_{sit} \, ,$$

where ρ_s is the coefficient of autocorrelation for segment s, and u_{sit} are independently normally distributed error terms with mean 0 and variance σ_s^2. For this variance structure, ordinary least squares (OLS) estimators are not efficient and the tests of significance performed on OLS estimators are not valid. Therefore, we use maximum likelihood estimation (MLE) to estimate the parameters of our model[2]. We solve the MLE problem using the computationally efficient algorithm devised by Beach and MacKinnon (1978). Further details about the estimation methodology can also be found in Greene (1997), and a survey of the research on the asymptotic properties of various estimation methods can be found in Judge, et al. (1985).

3.3 Results and Discussion

In this section, we first discuss the fit statistics and tests of hypotheses for models 1 and 2. In §3.3.2, we discuss econometric issues to determine which specifications of the control variables and the variance of the error term are appropriate for the model.

3.3.1 Basic Results

Table 3 shows the fit statistics for models 1 and 2 estimated using MLE. The overall fit of model 1 is statistically significant ($p<0.0001$). The coefficients of all the explanatory variables, logMU, logCI and logSS, are also significantly different from zero ($p<0.0001$).

Comparing the results for models 1 and 2, we find that the coefficients differ significantly across segments because the likelihood ratio test that model 1 is preferred to model 2 is significant ($p<0.0001$). Separate F-tests to determine whether each coefficient differs across segments are also significant ($p=0.0004$ for logMU, $p<0.0001$ for logCI, and $p<0.0001$ for logSS).

[2] Other estimation techniques that may be used include feasible generalized least squares (FGLS) estimation omitting the first observation for each firm (the Cochrane-Orcutt procedure or the Hildreth-Liu procedure) or full FGLS estimation using the Prais-Winsten transform. We do not omit the first observation in the time-series of each firm because our data have relatively short time-series and it has been shown that discarding the first observation can adversely affect the efficiency of the estimates when the length of the time-series is short. Instead, we apply the transformation $\varepsilon_{si1} = u_{si1} / \sqrt{1-\rho_s^2}$ to the first observation.

We determine the fraction of variation in logIT explained by each model by computing the overall prediction accuracy and the within-firm prediction accuracy of each model using the usual formula for R^2:

$$\text{Overall prediction accuracy} = 1 - \frac{\sum_{s,i,t}\left(\log IT_{sit} - \widehat{\log IT}_{sit}\right)^2}{\sum_{s,i,t}\left(\log IT_{sit} - \overline{\log IT}\right)^2},$$

$$\text{Within-firm prediction accuracy} = 1 - \frac{\sum_{s,i,t}\left(\log IT_{sit} - \widehat{\log IT}_{sit}\right)^2}{\sum_{s,i,t}\left(\log IT_{sit} - \overline{\log IT}_{si}\right)^2},$$

where $\widehat{\log IT}_{sit}$ is the predicted value of $\log IT_{sit}$ obtained from (1) or (2), $\overline{\log IT}$ is the overall mean of $\log IT_{sit}$, and $\overline{\log IT}_{si}$ is the within-firm mean of $\log IT_{sit}$[3]. The overall prediction accuracy for model (1) is 97.16% and for model (2) is 96.83%. The within-firm prediction accuracy for model (1) is 66.7% and for model (2) is 62.8%. The within-firm accuracy is remarkable because it shows that the regressors in our model explain a substantial 66.7% of the variation in the inventory turnover of a firm. The overall prediction accuracy is higher than the within-firm accuracy because the between-firm variation is larger than the within-firm variation, and moreover, is largely explained by the firm-specific fixed effects.

Table 4 shows the coefficients' estimates for models (1) and (2). The pooled coefficient for logMU is –0.2431 (p<0.0001). The estimate strongly supports hypothesis 1, that inventory turnover is negatively correlated with markup. According to the coefficient estimate, a 1% change in markup is associated with a –0.24% change in inventory turnover. Thus, firms that increased their markup realized an average decline of 0.24% in their IT on each percent increase in markup.

[3] There are several different measures of R-square for the generalized regression model. One alternative would be to apply the formula for R-square to the transformed model obtained in FGLS estimation. Since the R-square thus determined need not lie between 0 and 1, we do not use this procedure. See Kmenta (1996: chapter 12) for details.

The pooled coefficient for logCI is 0.25 ($p<0.0001$), and that for logSS is 0.143 ($p<0.0001$). These estimates strongly support hypotheses 2 and 3, respectively.

The pooled coefficient estimates are based on the assumption that the coefficients do not vary across segments. However, as shown in table 3, the differences between the coefficients across segments are statistically significant. Therefore, the pooled coefficients should be interpreted only as overall averages. The rest of table 4 shows the estimates of the coefficients for each segment. These estimates also strongly support hypotheses 1-3. Using two-sided t-tests, the coefficient of logMU has $p<0.001$ for 9 of the 10 segments, the coefficient of logCI has $p<0.001$ for 6 of the 10 segments, and the coefficient of logSS has $p<0.001$ for all ten segments. All of the estimates that are significant have signs in the directions predicted by the hypotheses. Possible reasons for the lack of significance of the coefficients for some segments are that there are fewer observations or more outliers in these segments. The outliers do not affect the pooled estimates because of the larger number of observations.

3.3.2 Econometric issues

Heteroscedasticity and autocorrelation in the error term

Segment-wise heteroscedasticity and first order autocorrelation are statistically significant in our dataset[4]. Table 5 gives the estimates of standard error and autocorrelation coefficient for each segment obtained for models 1 and 2. The standard error ranges from 0.011 for department stores to 0.145 for home furnishings and equipment stores. The autocorrelation coefficient ranges from 0.29 for hobby toys and games stores to 0.92 for home furnishings and equipment stores. Thus, the use of MLE with segment-wise heteroscedastic and AR(1) autocorrelated errors is suitable for our analysis.

Effects of different specifications of the fixed effects

Table 3 shows that the firm-wise fixed effects F_i and time-specific fixed effects c_t are statistically significant. Further, by estimating a model with interaction effects between segments and years, we find

[4] Upon estimating models 1-3 with and without the assumptions of segment-wise heteroscedasticity and AR(1) autocorrelation, we find that the value of the log likelihood function improves significantly (likelihood ratio test $p<0.0001$) after these assumptions. White's General Test for heteroscedasticity and Durbin-Watson test for AR(1) autocorrelation are also significant.

that c_t do not vary significantly across segments, and thus, need not be estimated separately for each segment. The estimates of c_t are shown in table 6. They have a significant downward trend with time. We comment on this finding in §4.1.

4 Evaluation of Retail Inventory Productivity

We use the results of our model to measure time-trends in inventory productivity in §4.1. In §4.2, we describe a new metric to evaluate inventory productivity, adjusted inventory turnover, and illustrate its use with examples. All the results in this section are obtained using pooled estimates from model 2 because the segment-wise coefficients are not statistically significant for some segments.

4.1 Time-trends in inventory productivity

We find that the overall trend in inventory turnover in our dataset is negatively sloping during 1985-2000. However, capital intensity has increased significantly during this period. Since capital intensity is positively correlated with inventory turnover as shown in §3, we find that the time-trend in inventory turnover controlling for the changes in markup, capital intensity and sales surprise, as measured by c_t in models 1 and 2, is negatively sloping.

We first examine time-trends in IT in an intuitive but somewhat imprecise way. Figure 1 shows a plot of average annual IT for our dataset for the years 1985-2000. Average annual IT for each year is computed in two ways: as an average of IT_{sit} of all firms for that year, and as the ratio of average CGS_{sit} to average Inv_{sit} of all firms for that year. We do not find any discernible time-trend in average IT. However, this method is imprecise because it fails to control for unequal time histories of firms and it does not separate time-trends from the effects of the covariates, MU, CI and SS.

Therefore, we compute 'unadjusted' time trends in IT, CI and MU ignoring the correlation between them by fitting the following model:

$$y_{sit} = a_i + bt + \nu_{sit}. \tag{4}$$

Here, y_{sit} equals IT_{sit}, CI_{sit} or MU_{sit} to estimate linear time-trends in the three variables, and $\log IT_{sit}$, CI_{sit} or MU_{sit} to estimate exponential time-trends. a_i is the intercept for firm i, and b is the common slope with respect to time across all firms. Thus, $b>0$ implies an upward trend in y_{sit} and $b<0$ implies a downward trend. Table 7 gives the results obtained. We find that inventory turnover has decreased significantly with time, capital intensity has increased significantly with time, and markup has no significant time-trend.

The time-trend in inventory productivity after adjusting for the correlation between IT, MU, CI and SS can be estimated using the year-specific fixed effects, c_t, in models 1 and 2. Table 6 shows the estimates of c_t obtained from both the models, and figure 2 shows a time-series plot of c_t for model 2. The estimates have a significant negative slope with time. Further, taking the standard errors of the estimates into account, we find that the estimates for years 1987-1993 are significantly larger than the estimates for years 1996-2000. Thus, inventory turnover controlled for changes in capital intensity, markup and sales surprise has decreased with time.

We note that while the aggregate trend in inventory productivity is downward sloping, there are several firms that have improved their inventory productivity with time. Examples are presented in §4.2.

4.2 Adjusted Inventory Turnover: A Measure of Inventory Productivity

The results of §3 show that changes in net markup, capital intensity and sales surprise should be used in the evaluation of inventory productivity of a firm. We define the adjusted inventory turnover, AIT_{sit}, of firm i in segment s in year t by the equation

$$\log AIT_{sit} = \log IT_{sit} - b^1 \log MU_{sit} - b^2 \log CI_{sit} - b^3 \log SS_{sit}.$$

This equation adjusts the inventory turnover of the firm for differences in MU, CI and SS by using the slope coefficients obtained from model 2. Thus, it enables comparison of inventory productivity over time for a specific firm as well as across firms for specific years.

We equivalently write AIT_{sit} as[5]

$$AIT_{sit} = IT_{sit} \left(MU_{sit}\right)^{-b^1} \left(CI_{sit}\right)^{-b^2} \left(SS_{sit}\right)^{-b^3}. \tag{5}$$

[5] By the assumptions of maximum likelihood estimation in §3.2, $\log IT_{sit}$ is normally distributed. Thus, AIT_{sit} is lognormally distributed. We ignore the factor exp(variance/2) in estimating the mean of AIT_{sit} for simplicity. This factor is close to 1 due to the strong fit of the model.

We illustrate the insights obtained from using adjusted inventory turnover to benchmark inventory productivity by the following three examples. We use AIT without the subscripts s, i, t as an abbreviation for adjusted inventory turnover.

Example 1: Time-trends in IT and AIT.

This example compares time-trends in IT and AIT for three firms in the Variety Stores segment, Target Corporation, Wal-Mart Stores, Inc., and K-Mart Corporation. Figure 3(a) shows time-plots of IT for these firms for the period 1987-2000, figure 3(b) shows time-plots of AIT, and the legend below the figures gives the slopes of all the curves with respect to time. We observe that K-Mart had lower values of IT and AIT than the other two firms throughout the period. Comparing Target and Wal-Mart, we observe that Target's inventory turnover increased by a smaller amount than Wal-Mart's. However, its adjusted inventory turnover increased by a larger amount than Wal-Mart's. This is so because Target's markup increased during this period but Wal-Mart's markup declined.

Example 2: Intra-firm longitudinal comparison of inventory turnover: Ruddick Corp.

This example shows a firm whose inventory turnover and adjusted inventory turnover have different time-trends. Ruddick Corp. is a holding company which owns Harris Teeter, a regional supermarket chain in the southeastern United States with 137 stores and sales of $2.7 billion in the year 2000. Table 8 shows the MU, CI, SS, IT and AIT for Harris Teeter for each of the years 1987-2000. In addition, figure 4 shows time-series plots and linear trends of IT and AIT for Harris Teeter for the same period. By observing the values of inventory turnover, we would conclude that the inventory productivity of Harris Teeter has not improved with time because inventory turnover does not show any significant trend. It has declined from 9.1 in 1987 to 7.85 in 2000, but the decline is not statistically significant. However, after computing adjusted inventory turnover, we find that the inventory productivity of Harris Teeter has increased significantly at an average rate of 0.07 per year. This increase is attributed to the increase in markup of Harris Teeter from 0.31 to 0.45 during 1987-2000 while its average inventory turnover remained stationary.

Example 3: Comparison of inventory turnover between firms.

This example considers six firms in the apparel and accessories retail segment for which the comparisons of IT and AIT yield different conclusions. Table 9 shows the average values of MU, CI, SS, IT and AIT for these firms for the years 1987-2000.

1. Casual Male Retail Group sells quality branded apparel through 105 stores in outlet malls, direct mail and the internet (total sales $192 million). Syms Corp sells quality branded apparel through 45 "off-price" stores (total sales $284 million). The average inventory turnover of Syms Corp at 2.56 is much higher than that of Casual Male at 2.02. However, after adjusting for the differences in MU, CI and SS, we find that the two firms have similar values of average adjusted inventory turnover. This difference occurs because Casual Male has higher margins and lower capital intensity than Syms Corp.
2. Charming Shoppes, Inc., is a retail chain with 2446 stores and sales of $2230 million selling women's apparel. Chico's Fas, Inc., is a retail chain with 321 stores and sales of $415 million selling both men's and women's apparel. Both firms have similar average inventory turnover of about 4.0 during the period 1987-2000. However, their values of adjusted inventory turnover are dramatically different. Charming Shoppes has adjusted inventory turnover of 3.6, while Chico's Fas has adjusted inventory turnover of 4.8. This difference occurs because Charming Shoppes has lower margins than Chico's Fas.
3. Ann Taylor Stores Corp. is a women's apparel retailing chain with 538 stores and sales of $1340 million. Nordstrom, Inc., is a family apparel retailing chain with 149 stores and sales of $5660 million. Both firms have similar average inventory turnover of about 4.2 during the period 1987-2000. However, their values of adjusted inventory turnover are quite different. Nordstrom has adjusted inventory turnover of 3.9, while Ann Taylor has adjusted inventory turnover of 4.7. Ann Taylor's higher adjusted inventory turnover is attributed to a higher average markup and lower capital intensity.

5. Conclusions

We have presented an empirical model to determine the impact of various operational characteristics, markup, capital intensity and sales surprise, on inventory turnover. The model explains a substantial 66.7% of the variation in inventory turnover within a firm and 97.2% of the total variation in inventory turnover, within and across firms. Using this model, we have defined an alternative metric of inventory productivity, adjusted inventory turnover, which compensates inventory turnover for changes in markup, capital intensity and sales surprise. Adjusted inventory turnover is useful to managers because it can be used to benchmark inventory productivity across firms, over time or across product categories within a firm.

Since this paper is based on public financial data, it has some limitations that may be addressed in future research using more detailed observations. First, our measure of capital intensity includes investment in not only warehouses and technology, but also stores. The financial data may be supplemented with data on total square-footage of warehousing space and total square-footage of stores to obtain a more refined measure of capital intensity. Second, data on number of products and rate of introduction of new products may be collected to measure the degree of variety and the length of product lifecycle. Thus, one may determine the impact of these variables on inventory turnover and markup.

The results of this paper offer several opportunities for future empirical research on inventory productivity. First, our analysis can be replicated for manufacturing and wholesale distribution sectors to investigate the variation in inventory productivity and examine whether it has improved with time. Second, the differences in firm-wise fixed effects F_i and adjusted inventory turnover across firms can be used to analyze how some firms realize higher inventory productivity than others. Third, we have focused attention on the simultaneous relationship between capital intensity and inventory turnover, and have ignored lagged effects. Using different models, we can examine whether investment in capital assets led to larger improvements in inventory productivity over longer time periods. Fourth, adjusted inventory turnover can be used to investigate whether improvement in inventory productivity affects other performance indicators such as stock returns, incidence of bankruptcy, or long-term profitability.

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Appendix 1: Definition of Variables

Indices

Let s be the index for the segment that a firm belongs to, i denote the firm, t denote the year of the financial statement, and q = 1…4 denote the quarter in a given year.

Income Statement Variables

S_{sit} Sales of firm i in segment s in year t.

CGS_{sit} Cost of Goods Sold of firm i in segment s in year t. The difference between the sales and the cost of goods sold is termed as Gross Profit.

Balance Sheet Variables

GFA_{sitq} Gross Fixed Assets, comprised of Land, Property, and Equipment, of firm i in segment s at the end of quarter q in year t.

NFA_{sitq} Net Fixed Assets, comprised of Gross Fixed Assets less Accumulated Depreciation, of firm i in segment s at the end of quarter q in year t.

Inv_{sitq} Inventory, valued at cost, of firm i in segment s at the end of quarter q in year t.

TA_{sitq} Total Assets of firm i in segment s at the end of quarter q in year t $\equiv Inv_{sitq} + NFA_{sitq}$ + Account Receivables + Cash + Investments + Intangible assets such as goodwill.

Computed Performance Variables

IT_{sit} Inventory turnover (also called inventory turns) for firm i in segment s in year t, defined as the ratio of the total cost of goods sold in year t to the average amount of inventory in year t.

$$IT_{sit} = \frac{CGS_{sit}}{\frac{1}{4}\sum_{q=1}^{4} Inv_{sitq}}$$

MU_{sit} Net markup for firm i in segment s in year t, defined as the ratio of the gross profit earned in year t to the cost of goods sold in year t. The gross profit is given net of markdowns.

$$MU_{sit} = \frac{S_{sit} - CGS_{sit}}{CGS_{sit}}$$

CI_{sit} Capital intensity for firm i in segment s in year t, defined as the ratio of the average gross fixed assets in year t to the sum of the average inventory and the average gross fixed assets in year t. We divide by the sum of the average inventory and the average gross fixed assets in order to make CI_{sit} independent of scale. Alternatively, TA_{sit} or S_{sit} may be used as scaling factors. Further, NFA_{sitq} may be used in place of GFA_{sitq} to measure capital investment.

$$CI_{sit} = \frac{\sum_{q=1}^{4} GFA_{sitq}}{\sum_{q=1}^{4} Inv_{sitq} + \sum_{q=1}^{4} GFA_{sitq}}$$

SS_{sit} Sales surprise for firm i in segment s in year t, defined as the ratio of the sales in year t to the forecast of sales in year t using information up to year t-1. We use various methods for calculating sales forecast as described in §3.3.

$$SS_{sit} = \frac{S_{sit}}{\text{Sales Forecast}_{sit}}$$

Notes:

1. We use IT, MU, CI and SS without the subscripts s, i, t as abbreviations for the respective variable names.
2. In the computation of IT and CI, we calculate average inventory and average gross fixed assets using quarterly closing values in order to control for systematic seasonal changes in these variables during the year.

3. The interpretation of CI is as follows. A small value of CI implies that a firm has a larger investment in inventory than in its fixed assets. Since the gross fixed assets of the firm are comprised of investments in distribution centers, equipment, information systems, logistics, technology, stores, etc., thus, a small value of CI indicates that the firm is less capital intensive. On the contrary, a large value of CI implies that the firm has a smaller investment in inventory than in its fixed assets. Such a firm is more capital intensive.
4. The reader is referred to Stickney and Weil (1999) for detailed descriptions of the income statement and balance-sheet variables.

Appendix 2: The effect of a change in stocking level on expected inventory turnover

We consider the classical single-period newsboy model and show that expected inventory turnover decreases with the increase in stocking quantity. Let X be a random variable denoting demand, x be a realization of X, f(x) be the probability density function of X assumed to be continuous, F(X) be the cumulative distribution function of X, and q be the stocking quantity at the beginning of the period.

The realization of sales is equal to min{X,q}. The expected inventory turnover may be computed in two ways: it may either be defined as the ratio of expected sales to expected average inventory level,

$$E[IT] = \frac{E[\min\{X,q\}]}{q - E[\min\{X,q\}]/2}, \tag{A1}$$

or as the expectation of the ratio of realized sales to realized average inventory level,

$$E[IT] = E\left[\frac{\min\{X,q\}}{q - \min\{X,q\}/2}\right]. \tag{A2}$$

For both these definitions, we will show that

$$\frac{d}{dq}E[IT] \leq 0.$$

Thus, we will prove that expected inventory turnover decreases with the increase in stocking quantity for the classical newsboy model.

The following results are useful.

$$E[\min\{X, q\}] = \int_0^q x\,\mathrm{f}(x)dx + q\left(1 - \mathrm{F}(q)\right), \tag{A3}$$

and

$$\frac{d}{dq}E[\min\{X, q\}] = 1 - \mathrm{F}(q). \tag{A4}$$

Differentiating (A1) with respect to q and substituting (A3) and (A4), we have

$$\begin{aligned}\frac{d}{dq}E[IT] &= \frac{q\frac{d}{dq}E[\min\{X, q\}] - E[\min\{X, q\}]}{\left\{q - E[\min\{X, q\}]/2\right\}^2} \\ &= -\frac{\int_0^q x\,\mathrm{f}(x)dx}{\left\{q - E[\min\{X, q\}]/2\right\}^2} \\ &\le 0.\end{aligned}$$

Similarly, differentiating (A2) with respect to q and substituting (A3) and (A4), we have

$$\begin{aligned}\frac{d}{dq}E[IT] &= \frac{d}{dq}\left[\int_0^q \frac{x}{q - x/2}\mathrm{f}(x)dx + \int_q^\infty 2\,\mathrm{f}(x)dx\right] \\ &= -\int_0^q \frac{x}{\left(q - x/2\right)^2}\mathrm{f}(x)dx \\ &\le 0.\end{aligned}$$

Thus, we conclude that expected inventory turnover decreases with the increase in stocking quantity.

Table 1: Classification of data using SIC codes into retailing segments

Retail Industry Segment	SIC Codes	Examples of firms
Apparel And Accessory Stores	5600-5699	Ann Taylor, Gap, Filenes Basement, Limited
Catalog, Mail-Order Houses	5961	Amazon.com, Lands End, QVC, Spiegel
Department Stores	5311	Dillard's, Federated, Macy's, J. C. Penney, Sears
Drug & Proprietary Stores	5912	CVS, Eckerd, Rite Aid, Walgreen
Food Stores	5400, 5411	Albertsons, Hannaford Brothers, Kroger, Safeway
Hobby, Toy, And Game Shops	5945	Toys r us
Home Furniture & Equip Stores	5700	Bed bath & Beyond, Pier 1 Imports
Jewelry Stores	5944	Tiffany, Zale
Radio,TV,Cons Electr Stores	5731	Best Buy, Circuit City, Radio Shack, CompUSA
Variety Stores	5331	K-Mart, Target, Wal-Mart, Warehouse Club

Table 2: Summary Statistics of the Variables for each Retailing Segment

(The values for each variable are its mean and standard error for the respective segment.)

Retail Industry Segment	Number of firms	Number of annual observations	Average Sales ($ million)	Inventory Turnover	Markup	Capital Intensity
Apparel And Accessory Stores	72	786	979.1	4.5732	0.6090	0.5897
				2.1348	0.2540	0.1381
Catalog, Mail-Order Houses	45	441	439.9	8.5985	0.8545	0.4980
				9.1104	1.0233	0.1806
Department Stores	23	309	6,058.6	3.8714	0.5232	0.6268
				1.4454	0.1553	0.1002
Drug & Proprietary Stores	23	256	2,309.5	5.2627	0.4119	0.4754
				2.8954	0.1532	0.1242
Food Stores	57	650	4,573.6	10.7769	0.3634	0.7509
				4.5767	0.1165	0.0843
Hobby, Toy, And Game Shops	10	98	1,455.5	2.9852	0.5610	0.4565
				1.0810	0.1608	0.1377
Home Furniture & Equip Stores	13	125	391.2	5.4431	0.7084	0.5458
				10.4296	0.2840	0.1611
Jewelry Stores	15	156	475.2	1.6802	0.7976	0.3581
				0.5823	0.3600	0.1111
Radio,TV, Cons Electr Stores	17	200	1,585.0	4.0951	0.4953	0.4361
				1.5353	0.2984	0.0919
Variety Stores	36	386	6,548.7	4.4526	0.4247	0.5064
				2.9245	0.1821	0.1524
Aggregate statistics	311	3407	2,791.4	6.0773	0.5561	0.5696
				5.4059	0.4522	0.1705

Table 3: Fit statistics for the maximum likelihood estimates of models 1 and 2

	Model 1	Model 2
-2*Log likelihood ratio	-4335.3	-3948.6
	(chi-sq = 2307.31)	(chi-sq = 2212.33)
AIC	-3589.3	-3256.6
AICC	-3473.1	-3157.7
BIC	-2195.6	-1963.8
Tests of significance of variables (F-tests)		
Firm	14.15	20.12
Year	6.17	4.29
log MU	172.97	353.72
log CI	128.92	140.31
log SS	457.69	411.18
Differences in coefficient estimates across segments (F-tests)		
log MU	3.77 (p=0.0004)	
log CI	30.86	
log SS	12.48	

Note: All the statistics are significant with $p<0.0001$ unless otherwise noted.

Table 4: Coefficients' estimates for models 1 and 2 obtained from MLE
(Pooled coefficients are for model 2 and segment-wise coefficients are for model 1.)

	log MU		log CI		log SS	
	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Coefficients from model 1						
Apparel And Accessory Stores	-0.137	0.02532	0.9689	0.06821	0.05311	0.01131
Catalog, Mail-Order Houses	-0.2377	0.03907	-0.04648*	0.09942	0.2242	0.02081
Department Stores	-0.2544	0.02323	0.8593	0.1018	0.1882	0.02009
Drug & Proprietary Stores	-0.1916	0.05555	0.3684	0.09287	0.1429	0.02432
Food Stores	-0.2992	0.03442	1.0911	0.09612	0.1784	0.01611
Hobby, Toy, And Game Shops	-0.3855	0.09807	-0.01725*	0.1514	0.2147	0.03313
Home Furniture & Equip Stores	-0.00955*	0.1008	0.5613**	0.2406	0.1739	0.03033
Jewelry Stores	-0.3507	0.05921	0.02605*	0.06275	0.2809	0.03389
Radio,TV,Cons Electr Stores	-0.3105	0.0545	0.2619	0.05857	0.1358	0.0341
Variety Stores	-0.2729	0.03727	0.1079	0.02812	0.1815	0.02662
Pooled coefficients from model 2	-0.2431	0.01293	0.2502	0.02112	0.143	0.007054

Note: Coefficients marked * are not significant, coefficients marked ** have $p<0.02$, all other coefficients have $p<0.001$.

Table 5: Segment-wise standard errors and autocorrelation coefficients for models 1 and 2

	Model 1		Model 2	
Retail Industry Segment	σ_s^2	ρ_s	σ_s^2	ρ_s
Apparel And Accessory Stores	0.01985	0.6950	0.02362	0.6517
	0.001808	0.03016	0.002028	0.03256
Catalog, Mail-Order Houses	0.08934	0.5960	0.09029	0.5629
	0.009582	0.04708	0.009198	0.04756
Department Stores	0.01102	0.6574	0.01494	0.7193
	0.001535	0.05074	0.002322	0.0463
Drug & Proprietary Stores	0.03198	0.7669	0.03054	0.7561
	0.00555	0.04271	0.005182	0.04356
Food Stores	0.01636	0.7718	0.01881	0.7700
	0.001774	0.02615	0.00204	0.02636
Hobby, Toy, And Game Shops	0.01539	0.3139	0.01816	0.2861
	0.002685	0.1112	0.003128	0.1079
Home Furniture & Equip Stores	0.1364	0.9228	0.1453	0.9215
	0.04627	0.02853	0.04885	0.02872
Jewelry Stores	0.01947	0.5314	0.02519	0.5527
	0.003296	0.08592	0.00451	0.08857
Radio,TV,Cons Electr Stores	0.02161	0.8171	0.02089	0.8118
	0.004679	0.04219	0.004475	0.04297
Variety Stores	0.01774	0.7518	0.01982	0.7582
	0.002489	0.03756	0.002778	0.03549

Note: Standard errors are reported below the coefficients' estimates.

Table 6: Estimates of time-specific fixed effects c_t for models 1 and 2

Year	Model 1		Model 2	
	Estimate	Std. Error	Estimate	Std. Error
1987	0.1297	0.0171	0.1009	0.0181
1988	0.0890	0.0168	0.0611	0.0177
1989	0.0774	0.0164	0.0423	0.0173
1990	0.0697	0.0160	0.0375	0.0169
1991	0.0681	0.0155	0.0460	0.0164
1992	0.0586	0.0150	0.0388	0.0159
1993	0.0517	0.0146	0.0363	0.0155
1994	0.0380	0.0141	0.0276**	0.0150
1995	0.0287**	0.0136	0.0174*	0.0145
1996	0.0109*	0.0129	0.0008*	0.0139
1997	0.0119*	0.0121	-0.0009*	0.0129
1998	0.0044*	0.0108	-0.0024*	0.0116
1999	0.0000*	0.0086	-0.0024*	0.0093
2000	-		-	

Note: The coefficients marked * are not statistically significant. Those marked ** have $p<0.10$. All other coefficients have $p<0.01$.

Table 7: Time trends in IT, CI and MU estimated using equation (4)

Variable	Coefficient	Std Error	t-statistic	p-value
IT	-0.05460	0.01354	-4.03	<0.0001
log IT	-0.00454	0.00110	-4.11	<0.0001
CI	0.00568	0.00030	19.00	<0.0001
log CI	0.01250	0.00077	16.23	<0.0001
MU	-0.00187	0.00105	-1.78	0.0747
log MU	0.00167	0.00130	1.29	0.1973

Table 8: Annual adjusted inventory turnover for Ruddick Corp.

Year	MU	CI	SS	IT	AIT_{sit}
1987	0.3058	0.7334	1.0970	9.0984	6.5766
1988	0.3133	0.7228	1.0338	8.0815	6.1894
1989	0.3235	0.7313	1.0368	8.1788	6.4111
1990	0.3270	0.7447	0.9279	8.4994	6.7879
1991	0.3444	0.7496	0.9505	8.1667	6.5167
1992	0.3529	0.7505	1.0217	7.9681	6.3734
1993	0.3623	0.7466	1.0399	7.8878	6.3579
1994	0.3667	0.7472	0.9977	7.9357	6.5084
1995	0.3966	0.7622	0.9850	8.1721	6.8800
1996	0.4208	0.7810	0.9535	8.2463	7.1503
1997	0.4294	0.7947	1.0376	8.4759	7.2776
1998	0.4330	0.8034	1.0073	8.5203	7.3528
1999	0.4368	0.8100	0.9758	8.3971	7.2803
2000	0.4476	0.8129	0.9686	7.8474	6.8291

Table 9: Comparison of inventory turnover between firms

	MU	CI	SS	IT	AIT_{sit}
Casual Male Retail Group	0.710	0.342	1.035	2.022	2.380
Syms Corp	0.554	0.666	0.998	2.563	2.355
Charming Shoppes	0.444	0.648	1.004	4.060	3.600
Chicos Fas Inc	1.550	0.728	1.031	4.031	4.799
Ann Taylor Stores Corp	0.989	0.615	1.004	4.255	4.713
Nordstrom Inc	0.588	0.730	0.990	4.210	3.893

Figure 1: Plot of annual average inventory turnover for the years 1985-2000

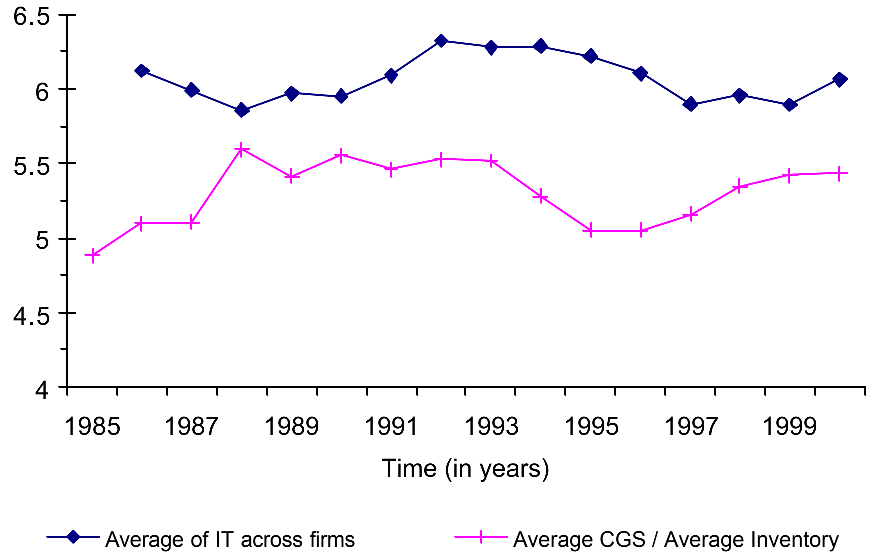


Figure 2: Plot of time-specific fixed effects c_t for model 2
(the error bars show intervals of 2*standard error)

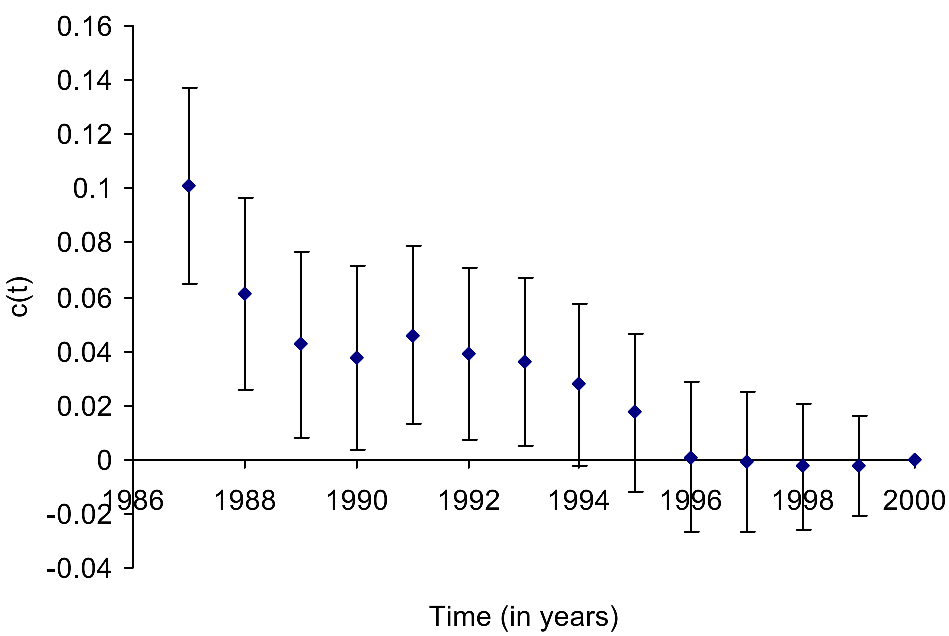
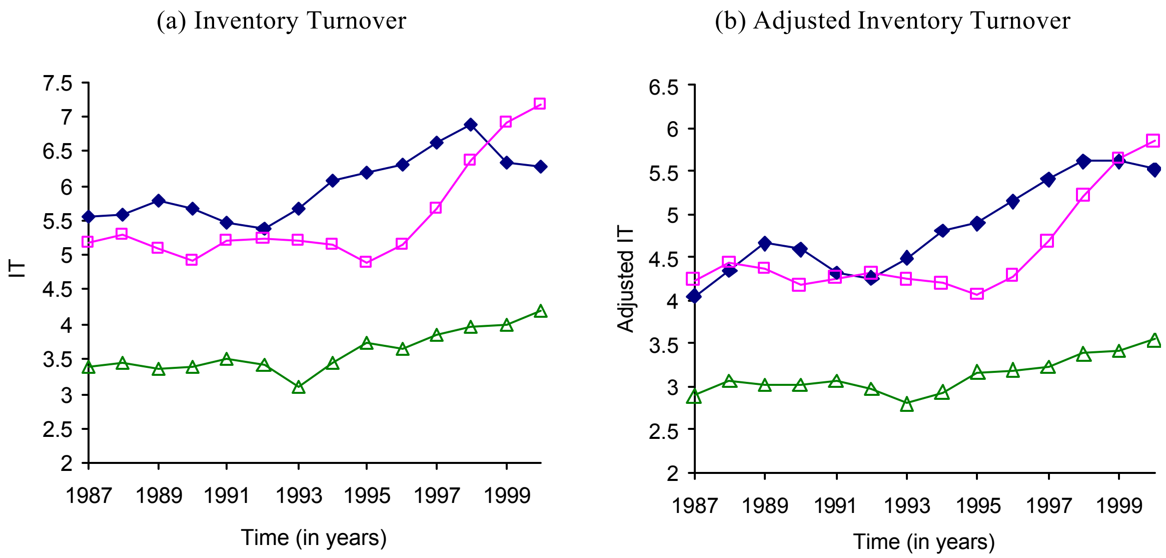


Figure 3: Plots of Inventory Turnover and Adjusted Inventory Turnover for Best Buy, Wal-Mart, Gap and K-Mart.



Legend

	Slope of IT	Slope of IT[a]
Target Corp.	0.0911	0.1184
Wal-Mart Stores	0.1307	0.0981
K-Mart Corp.	0.0604	0.0403

Figure 4: Plot of Inventory Turnover and Adjusted Inventory Turnover for Ruddick Corp.